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RESEARCH ARTICLE

J. LAKSHMI NARAYANA, K. SRI RAMA KRISHNA, L. PRATAP REDDY, G. V. SUBRAHMANYAM

Modeling of double ridge waveguide using ANN

Abstract The ridge waveguide is useful in various microwave applications because it can be operated at a lower frequency and has lower impedance and a wider mode separation than a simple rectangular waveguide. An accurate model is essential for the analysis and design of ridge waveguide that can be obtained using electromagnetic simulations. However, the electromagnetic simulation is expensive for its high computational cost. Therefore, artificial neural networks (ANNs) become very useful especially when several model evaluations are required during design and optimization. Recently, ANNs have been used for solving a wide variety of radio frequency (RF) and microwave computer-aided design (CAD) problems. Analysis and design of a double ridge waveguide has been presented in this paper using ANN forward and inverse models. For the analysis, a simple ANN forward model is used where the inputs are geometrical parameters and the outputs are electrical parameters. For the design of RF and microwave components, an inverse model is used where the inputs are electrical parameters and the outputs are geometrical parameters. This paper also presents a comparison of the direct inverse model and the proposed inverse model.

Keywords ridge waveguide, radio frequency (RF), computer-aided design (CAD), artificial neural network (ANN), forward and inverse models

1 Introduction

The waveguide used in many broadband microwave equipments is the ridge geometry. An important feature of this sort of waveguide compared to the conventional rectangular waveguide is the wider separation between the cutoff numbers of its dominant and the first higher-order mode. Another fact is that its impedance is bracketed between that of the rectangular waveguide (377 Ω) and those of coaxial and strip line structures (50 Ω) [1]. The original ridge waveguide consists of a rectangular waveguide with one or two ridge inserts. Most passive components that may be realized in conventional rectangular waveguides are also available in ridge geometry. Compared to rectangular waveguides, ridge waveguides [2,3] have the advantages of wide fundamental-mode operation bandwidth, low cutoff frequency, and low wave impedance. Fundamental mode operation bandwidth of five to one or more is easily obtainable with ridge waveguides. The low cutoff frequency yields a small cross-section and hence a compact size of ridge waveguide components. The low wave impedance permits an easy transition to planar transmission lines such as strip lines or micro-strip lines. In addition, there is a great deal of flexibility in ridge configuration according to different electrical and mechanical requirements [4]. Some common ridge configurations include single or double ridge, triple ridge, and single or double antipodal ridge. Because of these advantages, ridge waveguides have found extensive applications in microwave active and passive components, including filters.

Evanescent mode ridge waveguide filters have drawn considerable attention in the recent past because of their relatively wide spurious free out-of-band response, compact size, and reduced weight [5–7]. Recently, evanescent mode ridge waveguide bandpass filters are implemented successfully in low-temperature co-fired ceramics (LTCC) [8,9]. As mentioned above, compared to rectangular waveguides, ridge waveguides have a lower fundamental-mode cutoff frequency. Hence, ridge waveguide filters have a smaller cross-section than rectangular waveguide filters. However, the lengths of the two types of filters are comparable with each other. Many applications require ridge waveguide filters with substantially reduced length.

Figures 1(a) and 1(b) show the single and double ridge cross-sections; their equivalent circuit representation [3] is shown in Fig. 1(c). A ridge waveguide is more expensive

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J. LAKSHMI NARAYANA (✉), K. SRI RAMA KRISHNA,
L. PRATAP REDDY, G. V. SUBRAHMANYAM
Department of Electronics & Communication Engineering, St. Ann's College of Engineering and Technology, Chirala, A.P., India
E-mail: jln_9976@yahoo.com

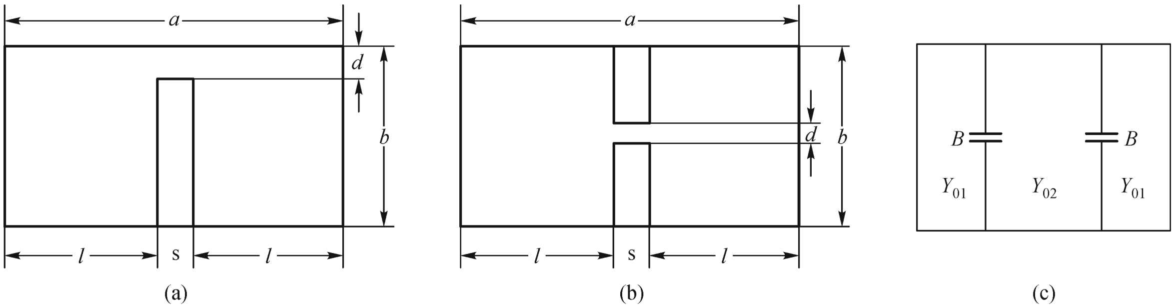

Fig. 1 Ridge waveguide. (a) Single ridge waveguide; (b) double ridge waveguide; (c) equivalent circuit

to manufacture than a standard rectangular waveguide; however, it allows operation at lower frequencies for a given size. Consequently, smaller overall waveguide dimensions are possible using a ridge waveguide.

Artificial neural networks (ANNs) are information processing systems with their design inspired by the studies of the ability of the human brain to learn from observations and to generalize by abstraction [10,11]. The fact that neural networks can be trained to learn any arbitrary nonlinear input-output relationships from corresponding data has resulted in their use in a number of areas such as pattern recognition, speech processing, control, biomedical engineering, etc. ANNs can also be applied to radio frequency (RF) and microwave computer-aided design (CAD) problems as well. A neural network model for microwave device/circuit can be developed from measured/simulated microwave data through a process called training after ANN architecture is set up. Once the ANN model is fully developed, the computation time is usually negligible and much faster than any single full-wave electromagnetic (EM) simulator. Although a considerable effort is required in developing an ANN model, it is worthy doing so if repeated design analysis and optimization is required.

This paper presents the analysis and design of a double ridge waveguide using ANN forward and inverse models. Performance of the proposed models is evaluated in terms of average and maximum estimated errors using different neural network training algorithms. The results of the proposed models are compared with that of the simulated results and presented graphically.

The remainder of the paper is organized as follows: Section 2 focuses on ANN modeling techniques for the analysis and design of double ridge waveguide. Section 3 explains proposed ANN inverse model for the design of double ridge waveguide. Finally, Section 4 summarizes the presented research work.

2 ANN modeling techniques

ANN represents a promising modeling technique, especially for data sets having nonlinear relationships that are frequently encountered in engineering [12–18]. In the course of developing an ANN model, the architecture of ANN and the learning algorithm are the two most important factors [19]. ANNs have many structures and architectures [20]. The class of ANN and/or architecture selected for a particular model implementation depends on the problem to be solved. ANN models are a kind of black box models, whose accuracy depends on the data presented to it during training. A good collection of the training data, i.e., data that is well distributed, sufficient, and accurately simulated, is the basic requirement to obtain an accurate model. For microwave applications, there are two types of data generators, namely, measurement and simulation.

In this paper, the multilayered perceptron (MLP) neural network architecture is used for the analysis and design of a double ridge waveguide. As discussed in Ref. [21], the reason for selecting MLP neural network (MLPNN) with three layers (input, hidden, and output) is to approximate any arbitrary nonlinear continuous multidimensional function to any desired accuracy.

2.1 ANN model for the analysis of double ridge waveguide (forward model)

A neural network trained to model original EM problems can be called the forward model where the inputs are physical or geometrical parameters and the outputs are electrical parameters. The sequential flow diagram for various steps involved in neural model development is presented in Ref. [22]. The neural network structure used in this paper is conventional MLP network, and the model development process is termed the MLPNN process. The flow diagram of this process is represented in Ref. [23]. MLPs have a simple layer structure in which successive layers of neurons are fully interconnected, with connection weights controlling the strength of the connections. The MLP comprises an input layer, an output layer, and a number of hidden layers. MLPs can be trained using many different learning algorithms.

A simple and accurate neural model (ANN forward model) is proposed for calculating the normalized cutoff wavelength (λ_c/a) of double ridge waveguide as shown in Fig. 2. The data sets used in this paper are obtained from

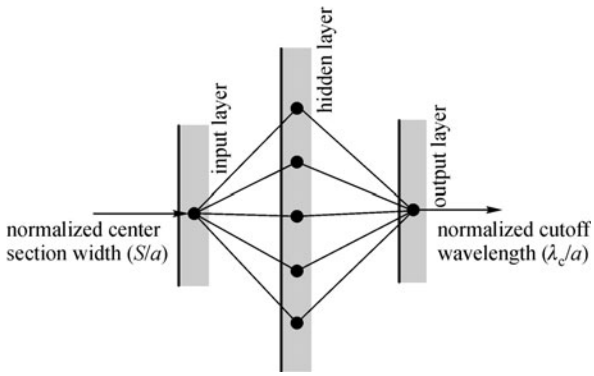

Fig. 2 Neural model for calculating normalized cutoff wavelength (λ_c/a) of a double ridge waveguide (forward model)

learning algorithms, namely, back propagation (BP), sparse training (ST), conjugate gradient (CG), adaptive back propagation (ABP), quasi-Newton MLP (QN-MLP), quasi-Newton (QN), Huber-quasi-Newton (HQN), autopilot (AP (MLP3)), and simplex method (SM) [12,13]. The training and test results obtained from the forward neural model are given in Table 1 from which it is clear that the results of the neural model trained by the AP and HQN algorithms are better than those of the neural model trained by other algorithms. To validate the neural model for the analysis of double ridge waveguide, comprehensive comparisons have been made. In these comparisons, the results obtained from the neural model trained by AP algorithm for the forward model are compared with simulated results and are presented graphically in Fig. 4.

the simulation software and contain 10000 samples. The training data sets used here are software simulated and contain 7500 samples.

The neural networks are trained with a learning rate of 0.1 for 1000 epochs. The aim of the training process is to minimize the training error between the target output and the actual output of the ANN. Selection of training parameters and the entire training process mostly depend on experience besides the type of problem at hand. A flow chart showing neural network training, neural model testing, and use of training, validation, and test data sets in ANN modeling is shown in Fig. 3. After several trials, it was found that three-layered network achieved the task in high accuracy. The most suitable network configuration found was 1:5:1 for the analysis double ridge waveguide. The proposed neural forward model is trained with nine

2.2 ANN model for the design of double ridge waveguide (direct inverse model)

A neural network trained to model original EM problems can be called the forward model where the model inputs are physical or geometrical parameters and the outputs are electrical parameters. For the design purpose, the information is often processed in the reverse direction in order to find the geometrical/physical parameters for given values of electrical parameters, which is called the inverse problem. There are two methods to solve the inverse problem, i.e., optimization method and direct inverse modeling method. In the optimization method, the EM simulator or the forward model is evaluated repetitively in order to find the optimal solutions of the geometrical parameters that can lead to a good match between modeled

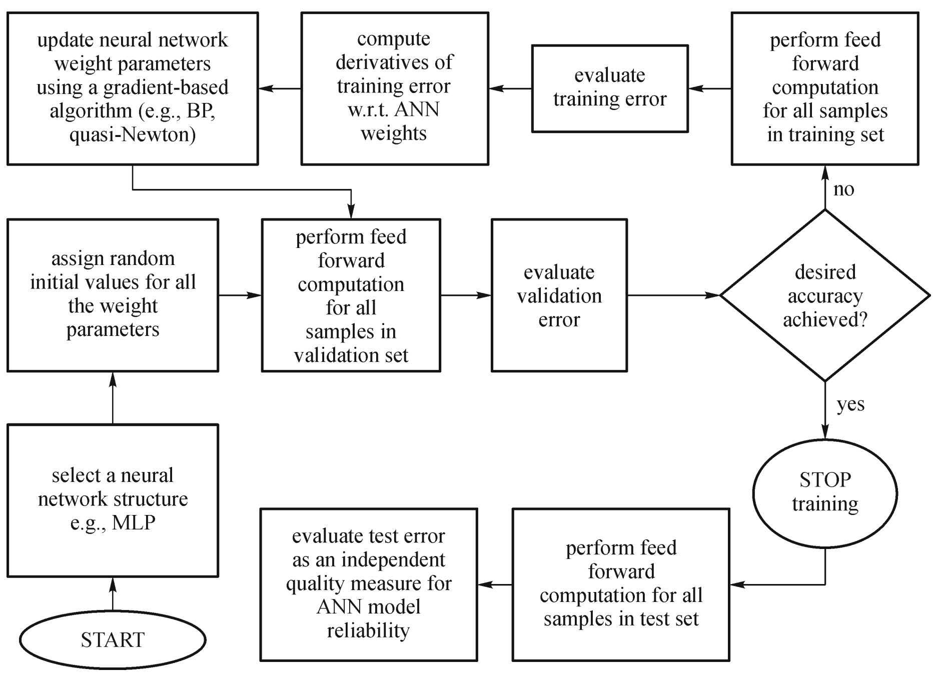

Fig. 3 Flow chart showing neural network training and neural model testing

Table 1 Training and test results for normalized cutoff wavelength (λ_c/a) of a double ridge waveguide of forward model

(a) Training results

learning algorithms	training error
BP (MLP3)	1.956149×10^{-3}
ST	10.154×10^{-3}
CG	1.87672×10^{-3}
ABP	2.12497×10^{-3}
QN (MLP)	2.970765×10^{-4}
QN	2.97211×10^{-4}
HQN	2.97064×10^{-4}
AP (MLP3)	2.970534×10^{-4}
SM	2.97979×10^{-4}

(b) Test results

learning algorithms	test		
	average error	worst case error	correlation coefficient
BP (MLP3)	0.19720	5.6249	0.99999154
ST	0.19720	5.6249	0.99999154
CG	0.18656	4.9089	0.99999213
ABP	0.19091	4.6103	0.99999243
QN (MLP)	0.03021	0.5872	0.99999976
QN	0.03016	0.5882	0.99999976
HQN	0.03016	0.5882	0.99999976
AP	0.03016	0.5882	0.99999976
SM	0.03054	0.5864	0.99999976

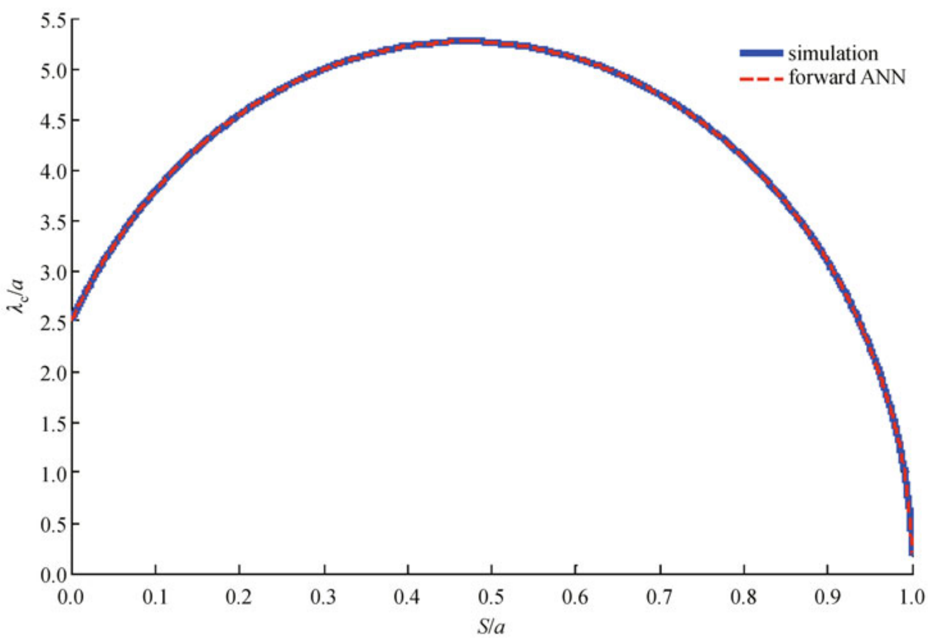

Fig. 4 Comparison of normalized center section width (S/a) vs. normalized cutoff wavelength (λ_c/a) obtained using the simulated results with that of the forward model of a double ridge waveguide

and specified electrical parameters. An example of such an approach is mentioned in Ref. [24]. This method of inverse modeling is also known as synthesis method. To compute the geometrical parameters from given electrical parameters is difficult to find analytically. Therefore, the neural network becomes a logical choice since it can be trained to learn from the data of the inverse problem. We define the input neurons of a neural network to be the electrical parameters of the modeling problem and the output neurons as the geometrical parameters. Training data for the neural network inverse model can be obtained simply by swapping the input and output data used to train the forward model. This method is called the direct inverse modeling and an example of this approach is discussed in Ref. [25]. Once training is completed, the direct inverse model can provide inverse solutions immediately unlike the optimization method where repetitive forward model evaluations are required. Therefore, the direct inverse model is faster than the optimization method using either the EM or the neural network forward model.

The neural network structure and the training algorithms that are used for the design of double ridge waveguide in direct inverse model is the same as that of forward model, which is discussed in the previous section, except swapping the input and output parameters. The neural model shown in Fig. 5 computes the normalized center section width (S/a) for a given normalized cutoff wavelength (λ_c/a). The training and test results obtained from the neural model are given in Table 2 from which it is clear that the results of the neural model trained by the SM and AP algorithms are found to be better for the direct inverse model.

To validate the neural model for the design of double

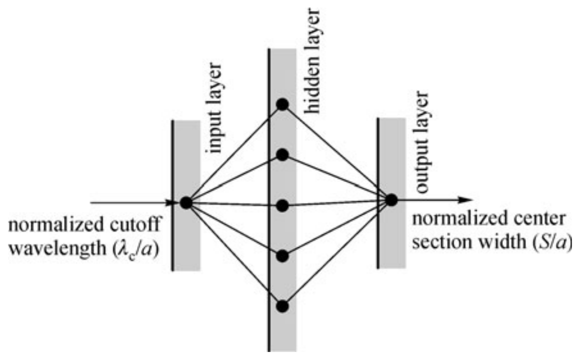

Fig. 5 Neural model for calculating normalized center section width (S/a) of a double ridge waveguide (direct inverse model)

Table 2 Training and test results for normalized center section width (S/a) of a double ridge waveguide of neural direct inverse model

(a) Training results

learning algorithms	training error
BP (MLP3)	0.221665
ST	0.228436
CG	0.221664
ABP	0.221677
QN (MLP)	0.2216687
QN	0.221668
HQN	0.221669
AP (MLP3)	0.2211581
SM	0.22017

(b) Test results

learning algorithms	test		
	average error	worst case error	correlation coefficient
BP (MLP3)	22.6392	64.369	0.88945603
ST	22.6392	64.369	0.88945603
CG	22.6391	64.365	0.88945590
ABP	22.6391	64.365	0.88945590
QN (MLP)	22.6392	64.394	0.88945675
QN	22.6392	64.394	0.88945675
HQN	22.6392	64.394	0.88945675
AP	22.5883	64.471	0.889604
SM	22.4855	66.064	0.89020866

ridge waveguide, comprehensive comparisons have been made. The results obtained from the neural model trained by SM for direct inverse model are compared with simulated results and are presented graphically in Fig. 6.

Although the neural network inverse model (direct inverse) can provide the solution faster than the optimization method, it often encounters the problem of non-uniqueness in the input-output relationship. It also causes difficulties during training, because the same input values to the inverse model will have different values at the output (multivalued solutions). Consequently, the neural network inverse model cannot be trained accurately. This is why training an inverse model may become more challenging than training a forward model.

As shown in Fig. 6, the response obtained from simulation software for the double ridge waveguide is non-monotonical in nature. From the graph, it was observed that the direct inverse neural network model is not suitable to solve for non-monotonical responses. The inverse model discussed in this section is suitable only for monotonical responses. Hence, there is a need to develop an ANN inverse model even for non-monotonical responses.

3 Proposed ANN inverse model for the design of double ridge waveguide (indirect inverse model)

As shown in Fig. 6, the graph obtained by direct inverse model is not the same as that of the simulated results. When the original forward input-output relationship is not monotonic, the non-uniqueness becomes an inherent problem in the inverse model. To solve this problem, we start by addressing multivalued solutions in training data [26]. If two different input values in the forward model lead to the same value of output, then a contradiction arises in the training data of the inverse model because the single input value in the inverse model (direct inverse) has two different output values. Since we cannot train the neural network inverse model to match two different output values simultaneously, the training error cannot be reduced to a small value. As a result, the trained inverse model (direct inverse) will not be accurate. The proposed method overcomes this problem. The overall methodology is summarized in the following steps [26]:

Step 1

Define the inputs and outputs of the model. Generate data using EM simulator or measurement. Swap the input and output data to obtain data for training inverse model. Train and test the inverse model. If the model accuracy is satisfied, then stop. Results obtained here is the direct inverse model.

Step 2

Segment the training data into smaller sections. If there have been several consecutive iterations between Steps 2 and 5, then go to Step 6.

Step 3

Train and test models individually with segmented data.

Step 4

If the accuracy of all the segmented models in Step 3 is satisfied, stop. Else for the segments that have not reached

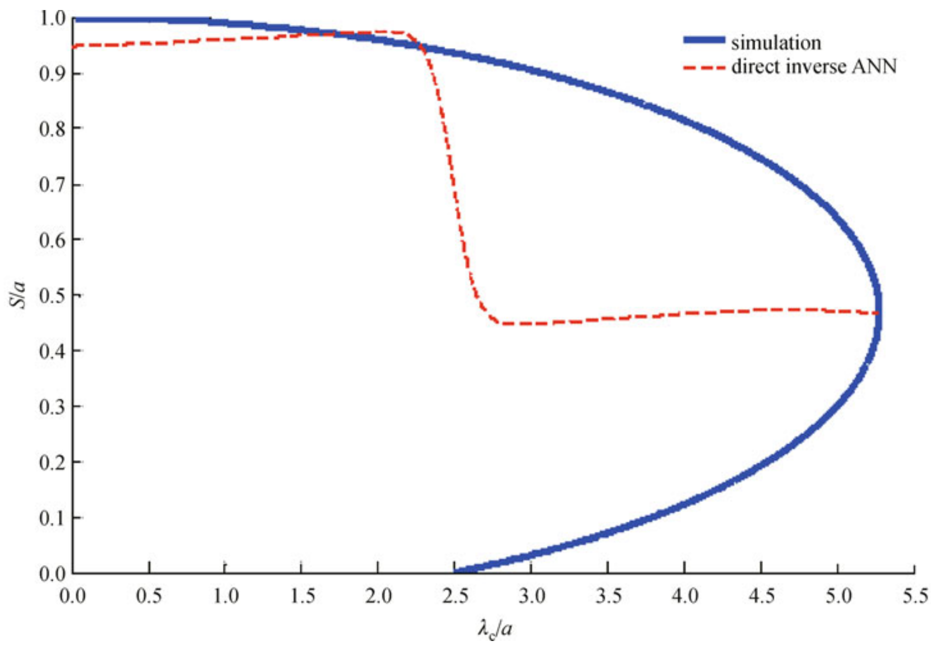

Fig. 6 Comparison of normalized cutoff wavelength (λ_c/a) vs. normalized center section width (S/a) obtained using the simulated results with that of the direct inverse model of a double ridge waveguide

accuracy requirements, proceed to the next steps.

Step 5

Check for multivalued solutions in the model's training data. If none are found, then perform further segmentation by going to Step 2.

Step 6

Train the neural network forward model.

Step 7

Using the adjoint neural network of the forward model, divide the training data according to derivative criteria.

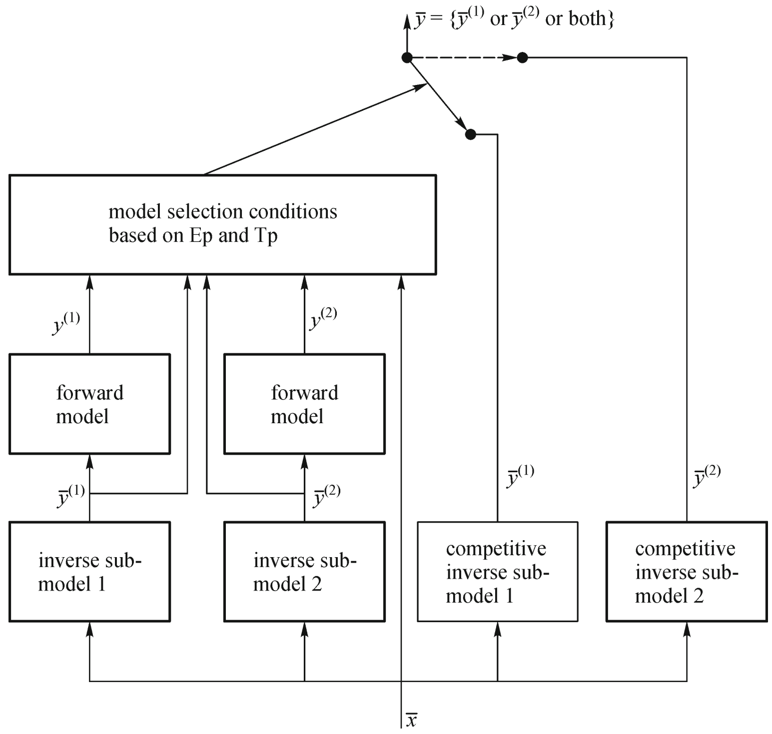

Fig. 7 Diagram of inverse model

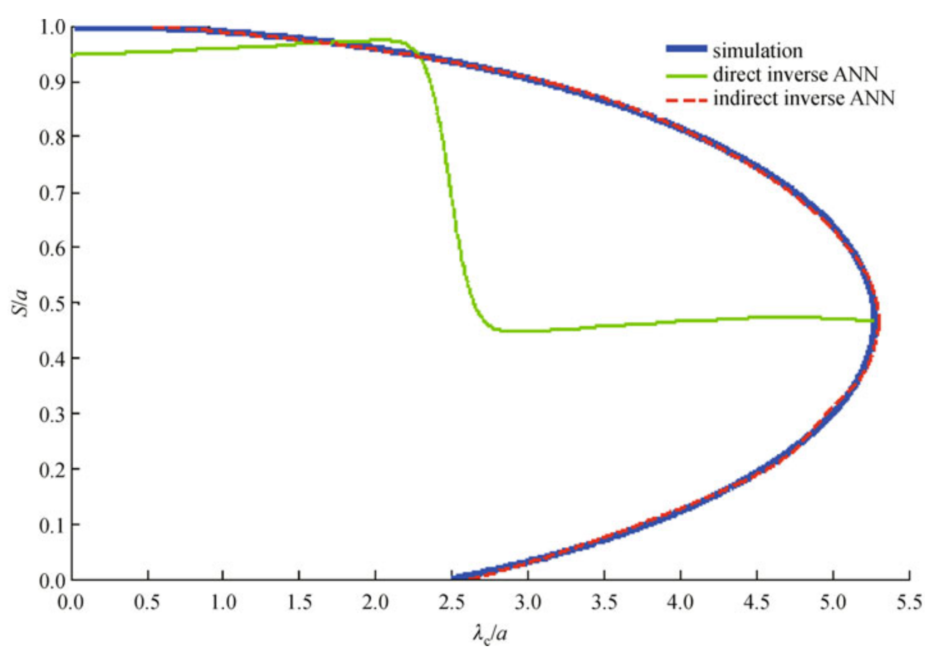

Fig. 8 Comparison of normalized cutoff wavelength (λ_c/a) vs. normalized center section width (S/a) obtained using the simulated results with that of the neural model (direct inverse model, proposed inverse model) of a double ridge waveguide

Step 8

With the divided data, train necessary sub-models, for example two inverse sub-models. Optionally obtain two competitively trained inverse sub-models and two forward sub-models.

Step 9

Combine all the sub-models that have been trained in Step 8. Test the combined inverse sub-models. If the test accuracy is achieved, then stop. Else go to Step 7 for further division of data according to derivative information in different dimensions, or if all the dimensions are exhausted, go to Step 2.

Figure 7 shows the proposed inverse model of a double ridge waveguide. Using the above model and following the steps discussed, the indirect inverse model is obtained. The response obtained by the inverse model (indirect inverse) is shown graphically in Fig. 8. From the graph, it is observed that the proposed inverse model is closely following the simulated results. The results obtained by the direct inverse model and proposed inverse model are compared graphically and are represented in Fig. 8.

4 Conclusion

Accurate and simple neural models are presented to compute the normalized cutoff wavelength (λ_c/a) and normalized center section width (S/a) of a double ridge waveguide using forward, direct inverse, and proposed inverse models. It has been observed that the proposed inverse model is giving better results when compared with the direct inverse model.

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